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Integrating partner objectives in horizontal logistics optimisation models☆

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ABSTRACT

In this paper a general solution framework is presented for optimising decisions in a horizontal logistics cooperation. The framework distinguishes between the objective of the group and the objectives of the individual partners in the coalition. Although the importance of the individual partner interests is often acknowledged in the literature, the proposed solution framework is the first to include these objectives directly into the objective function of the optimisation model. The solution framework is applied to a collaborative variant of the clustered vehicle routing problem, for which we also create a set of benchmark instances.

We find that by only considering a global coalition objective, the obtained solution is often suboptimal for some partners in the coalition. Providing a set of high quality alternative solutions that are Pareto efficient with respect to the partner objectives, gives additional insight in the sensitivity of a solution, which can support the decision making process. Our computational results therefore acknowledge the importance of including the individual partner objectives into the optimisation procedure.

1. Introduction

With every product or service only a couple of clicks away, logistics companies are challenged to rethink their operations. Driven by the evolution in e-commerce and the fact that many industries today rely on next-day and overnight just-in-time delivery services, the distribution planning tends to be highly dynamic and should, above all, be fast and efficient. In the last couple of years, horizontal logistics cooperation is increasingly considered to be a viable approach to lower cost and increase service levels. This form of collaboration can be defined as a long-term agreement between companies with similar or complementary transportation needs that aim to exploit synergies by means of active bundling and synchronisation of deliveries [33].

Most current research on horizontal logistics cooperation is focused on assessing the costs and benefits of the collaboration, and the allocation of these benefits among the individual collaborating partners. To estimate the potential benefits that result from horizontal logistics cooperation, researchers make use of simulation studies that are based on either theoretical instances [7,21,22], or on real life case studies [3,12,16]. For the allocation of the coalition cost or benefits, multiple allocation mechanisms have been described in the literature, ranging from cooperative game theoretical approaches to simpler rules of thumb [17,36].

Only a limited number of papers addresses operational planning problems in horizontal logistics cooperation (see Verdonck et al. [37] for an overview). Those papers generally assume a situation in which a group of partners, each with a set of delivery requests, form a coalition in which requests can be exchanged between partners. When quantifying the cost saving of such logistics collaborations, the non-collaborative (stand-alone) scenario is compared with a solution for the coalition. This collaborative solution is usually determined by aggregating all transportation requests of the individual partners into one large-scale optimisation problem, which is then solved with existing (non-collaborative) techniques. As a result, existing models do not take into account to which partner a transportation request originally belonged. One of the consequences of this is that no distinction is made between the objective of the coalition and the objective of each individual company. Although the coalition as a whole should perform as efficiently as possible to exploit the synergies from the collaboration, all collaborating partners remain independent entities that tend to favour a solution that is best according to their own objectives. Defryn and Sörensen [11] are the first to argue that both objective lev-

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els should be taken into account. They do not, however, propose a modelling framework and solution method to integrate both levels of decision making. To the best of our knowledge the current paper is the first to consider both objective levels simultaneously when optimising the logistics planning of a horizontal collaboration.

Our proposed solution approach is applied to the case of a cooperation of courier companies, in which the optimisation problem is modelled as a clustered vehicle routing problem. In Section 2, the current state of the art in operational optimisation in the context of a horizontal logistics cooperation is summarised. Section 3 contains the problem statement and introduces the clustered vehicle routing problem (CluVRP). Our integrated solution approach is introduced in Section 4 after which it is applied to the CluVRP. In this section, we also focus on the algorithmic implementation of the integrated solution approach for the CluVRP after which we elaborate on our obtained simulation results in Section 5. Finally, our conclusions and directions for further research are presented in Section 6.

2. Literature review

In the literature on the operational aspects of horizontal logistics optimisation two main approaches are distinguished: order sharing and capacity sharing [37]. In the first approach, each collaborating partner can decide to share (a selection of) its customer orders with the group. These pooled orders are then reallocated to the available vehicle trips. When the optimisation is done by solving one large-scale vehicle routing problem from the point of view of a centralised decision maker, this is referred to as *joint route planning* [7]. Another commonly used technique to reallocate customer orders is an *auction-based mechanism*, in which partners can bid on the pooled orders. See for example the framework provided by Dai and Chen [9]. In a second approach, companies can decide to share their vehicle capacities. In this way the capital investment associated with these vehicles can be split among multiple partners [37]. Because capacity sharing is less common in the literature and the results are similar to order sharing, our paper and therefore also all remaining references are focused on order sharing applications.

Usually, the benefits of horizontal logistics cooperation are qualified by comparing the logistics planning with and without collaboration. To obtain the collaborative solution, a logistics optimisation problem is to be defined and solved for the group of collaborating partners. Using the Web of Science, 59 journal publications on the topic of ‘horizontal cooperation’ (or ‘horizontal collaboration’) and ‘logistics’ were retrieved. Careful screening on the title and the abstract yielded a subset of 20 papers for further study. Moreover, we performed an additional manual search using the same keywords, resulting in a final set of 24 publications.

All studied papers are listed in Table 1. Each reference is categorised by the objective function used in the logistics optimisation model and the way in which the individual partner interest are handled. For the objective functions, four main approaches can be distinguished of which the minimisation of the distance-based routing cost *(min. dist.)* and the minimisation of the total logistics cost *(min. TC)* are the most common. Typically, this total logistics cost consists of the distance-based cost increased with additional factors such as a time-based cost [2,8,27], penalties for empty trips or non-delivery [2,13,19,27], additional linking costs when combining multiple transportation requests [1] or costs related to the use of DCs and warehouses [38,40]. Vanovermeire et al. [35] adopt an alternative approach in which the cost of a trip between two locations is calculated by means of a pace list. This means that the cost of a transport between two locations depends on the load of the vehicle with typically decreasing marginal costs. The optimisation model requires the solution of a bin packing problem in which the number of required vehicles is minimised *(min. veh.)*. Instead of minimising the transportation cost, some authors aim at maximising the total profit *(max. prof.)* of the coalition [6,25,42]. When requiring that all transportation requests are executed, this approach is equivalent to the minimisation of the logistics costs.

We observe that, in all listed papers, the operational plan for the coalition is obtained by simply aggregating the transportation requests of all partners after which the optimisation is done with respect to one global objective function. Such a simplification might give rise to the following drawbacks and limitations:

- The coalition as a whole is considered the only entity and, as a result, the multi-partner nature of the collaboration and the fact that orders might belong to different companies are ignored. However, the collaborating partners remain independent companies that might have a different service strategy (e.g., guarantee certain service level, provide fast deliveries, being the cheapest,...) and evaluate the cooperation in terms of personal gains differently.
- Considering only objectives at the level of the coalition, on which all partners should agree, limits the applicability of the model in more realistic cases with a heterogeneous set of partners (i.e. partners have different objectives).
- The most optimal solution for the coalition as a whole is considered the best and only possible outcome for the collaborative planning.

These drawbacks are related to the fact that individual partner interests are either not taken into account, or are limited to interests that only affect the cost of the solution. For this we refer again to Table 1. All papers marked in the *post* column, e.g., only include a method for dividing the total coalition cost as a post-processing step after solving the logistics optimisation model. As a result, partner interests are not taken into account while constructing the collaborative logistics planning. The *comp.* column shows all papers in which a (monetary) compensation if given for exchanging a customer order, usually by adopting an auction-based decentralised view. Here, partners can bid on individual transportation requests pooled by other partners and a transfer price (e.g., based on the winning bid) is considered together with the request exchange. Such an approach ignores the fact that companies might have other objectives that can not be compensated with such a side payment. In many cases, e.g., it is undesirable or even infeasible for practitioners to translate time window constraints into costs. Finally, Vanovermeire and Sörensen [34] add the constraint of individual rationality directly to the logistics optimisation model (see *const.* column). In this way, the authors ensure that an individual partner is rewarded for allowing a shift in delivery date so the coalition can achieve a better solution. Although this might help to partially overcome the third limitation, it does not sufficiently address the first two limitations nor is this applicable if the objective is not cost-related.

Additionally, it could be that some objectives are not shared among the collaborating partners or do not receive the same weight. For example, it is possible that respecting time windows is more important for one partner, while the other partners prefer the lowest cost. Also, a partner might prefer a solution in which its allocated cost is minimised above a solution with the lowest total cost for the coalition as a whole. We refer to Bailey et al. [4], for a logistics optimisation model for a coalition in which only the objective of one particular partner of interest is considered.

With this paper, we are the first to propose a multi-partner logistics optimisation framework that allows each individual partner to specify any possible objective. Moreover, by including one or multiple coalition objectives, we also consider the common goal(s) of the coalition during the logistics optimisation. Although this will give rise to a multi-objective logistics optimisation approach,

Table 1
Classification of the studied literature.

	Objective				Partner interests			
Reference	min. dist.	min. TC	min. veh	max. prof.	post	comp.	constr.	not
Cruijssen et al. [7]		✓						✓
Krajewska et al. [24]	✓				✓			
Berger and Bierwirth [6]				✓	✓			
Dahl and Derigs [8]		✓				✓		
Lozano et al. [27]		✓			✓			
Adenso-Díaz et al. [2]		✓						✓
Adenso-Díaz et al. [1]		✓						✓
Juan et al. [21]	✓							✓
Vanovermeire et al. [35]			✓		✓			
Vanovermeire and Sörensen [34]		✓					✓	
Wang and Kopfer [39]		✓						✓
Flisberg et al. [15]	✓				✓			
Li et al. [25]				✓		✓		
Pérez-Bernabeu et al. [29]	✓							✓
Wang et al. [41]		✓			✓			
Wang and Kopfer [40]	✓					✓		
Yang et al. [42]				✓		✓		
Defryn et al. [13]		✓			✓			
Guajardo et al. [18]	✓				✓			
Hezarkhani et al. [19]		✓			✓			
Kimms and Kozeletskyi [23]	✓				✓			
Verdonck et al. [38]		✓			✓			
Yin et al. [43]		✓						✓
Zibaei et al. [44]	✓				✓			

the added value of the paper is not the development of a multi-objective approach as such. Rather, the contribution of this paper is that (i) it clearly demonstrates the importance of both the coalition and the partner objectives, and (ii) provides a framework to take both types of objectives into account simultaneously. We provide the logistics decision maker with a limited set of solutions by focusing only on what we consider the most promising area of the solution space, while ensuring that the obtained solutions are not only of high quality for the coalition as a whole, but also satisfy the individual requirements of the collaborating partners. The framework is generic in the sense that any possible objective or combination of objectives could be considered at both levels. Moreover, it is designed to be straightforward, intuitive and transparent, so it can easily be implemented in practice.

3. Problem statement: the clustered vehicle routing problem

The solution framework for the integration of coalition objectives and partner objectives is defined in a general way in Section 4, and can be applied to any logistics optimisation problem. For illustrative purposes, the clustered vehicle routing problem (CluVRP) is used to show the principles of the presented solution framework.

The choice for the CluVRP can be motivated by the fact that we specifically aim to study horizontal cooperation in a distribution context. The increasing importance of e-commerce makes logistics optimisation more challenging, creating more opportunities for joint route planning. To handle the very large problem instances they face, courier companies use clustering to reduce problem complexity. The use of clusters (often referred to as zones) is acknowledged by many authors as a way to reduce the problem size and to avoid the need for detailed customer information during the planning phase [20,26,28,45]. The fact that individual customers are grouped together in predefined clusters, gives rise to a specific logistics optimisation problem, referred to as the clustered vehicle routing problem.

Introduced by Sevaux and Sörensen [30], the CluVRP is a generalization of the classical capacitated vehicle routing problem (CVRP) in which customers are grouped into predefined clusters. The problem is more constrained compared to the CVRP, as in the CluVRP all customers that belong to the same cluster should be served consecutively by the same vehicle.

3.1. Integer programming formulation

Consider a complete undirected graph $G = (V, E)$, where V is a set of vertices including one depot (denoted as V_0) and multiple customer nodes. A distance d_{ij}, is associated with each edge $(i, j) \in E$ connecting two nodes. We consider K to be a set of homogeneous vehicles with a maximum capacity Q each. All vehicles start and end their trip at the depot. For each customer i the demand is denoted by q_i. Furthermore, a set of clusters is defined and denoted by R. Cluster $r_0 \in R$ only contains one node, the depot. All other clusters contain at least one customer. The set of customers in a cluster is denoted as $C_r = \{i \in V \setminus V_0 : r_i = r\}, \ \forall r \in R$.

Following the formulation of Expósito-Izquierdo et al. [14], the CluVRP can be defined by the mathematical model described below. Consider Z to be any proper subset of V. Then, let $\delta^+(Z)$ be the set of edges $(i, j) \in Z \times V \setminus Z$ (i.e., the edges connecting all vertices in Z with the vertices not in Z, referred to as outgoing edges) and $\delta^-(Z)$ the set of edges $(i, j) \in V \setminus Z \times Z$ (i.e., the edges connecting all vertices outside of Z with all vertices in Z, referred to as incoming edges).

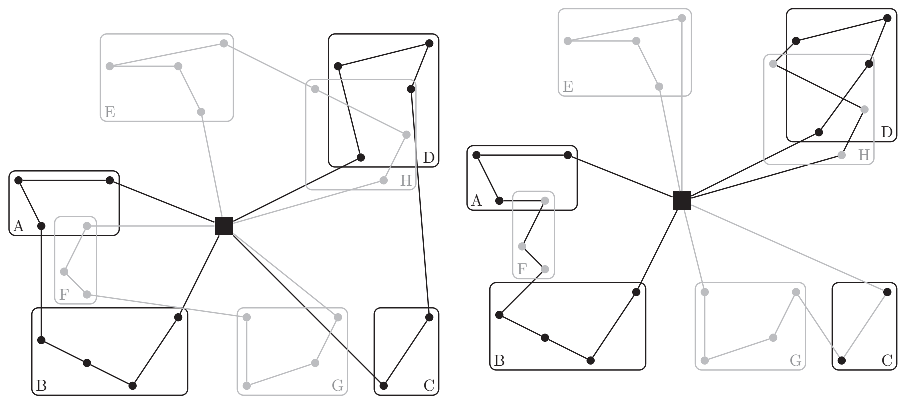
$$x_{ijk} = \begin{cases} 1 & \textit{vehicle } k \textit{ travels from node } i \textit{ to node } j \\ 0 & \textit{otherwise} \end{cases}$$

$$y_{ik} = \begin{cases} 1 & \textit{customer } i \textit{ is served by vehicle } k \\ 0 & \textit{otherwise} \end{cases}$$

$$\min \sum_{(i,j)\in E} \sum_{k\in K} d_{ij} x_{ijk} \tag{1}$$

Subject to

$$\sum_{k\in K} y_{ik} = 1 \qquad \forall i \in V \setminus V_0 \tag{2}$$



(a) Stand-alone scenario (b) Cooperative scenario with cluster ex-change

Fig. 1. The collaborative result for the clustered vehicle routing problem.

$$\sum_{k\in K} y_{0k} = |K| \tag{3}$$

$$\sum_{j\in V\setminus V_0} x_{ijk} = \sum_{j\in V\setminus V_0} x_{jik} = y_{ik} \qquad \forall k\in K, \forall i\in V \tag{4}$$

$$\sum_{i\in V} q_i y_{ik} \le Q \qquad \forall k\in K \tag{5}$$

$$\sum_{i\in Z}\sum_{j\notin Z} x_{ijk} \le y_{hk} \qquad \forall Z\subseteq V\setminus V_0, \forall h\in Z, \forall k\in K \tag{6}$$

$$\sum_{(i,j)\in\delta^+(C_r)}\sum_{k\in K} x_{ijk} = \sum_{(i,j)\in\delta^-(C_r)}\sum_{k\in K} x_{ijk} = 1 \qquad \forall r\in R \tag{7}$$

$$x_{ijk}\in\{0,1\} \qquad \forall (i,j)\in E, \forall k\in K \tag{8}$$

$$y_{ik}\in\{0,1\} \qquad \forall i\in V, \forall k\in K \tag{9}$$

In the model formulation above, the objective function given by Eq. (1) minimises the total distance travelled by all vehicles. Eq. (2) ensure that each customer is visited exactly once. Eq. (3) state that all vehicles should visit the depot. Eq. (4) guarantee that the same vehicle that arrives at a customer also leaves from that customer. Eq. (5) make sure that vehicle capacities are respected. The subtour elimination constraints are represented by Eq. (6). Eq. (7) establish that each cluster is visited exactly once by a single vehicle (i.e., there is exactly one incoming and one outgoing edge for the cluster r) and as a result that all customers in a cluster are visited consecutively. In what follows, the solution space bounded by Eqs. (2)–(9) is denoted as ζ. A solution vector x is said to be a feasible solution for the above-mentioned CluVRP if $x\in\zeta$.

3.2. The collaborative environment

We consider a grand coalition N, representing a horizontal cooperation between n courier companies $p\in N$. Let S be any subcoalition of N, such that $S\subseteq N$. In contrast to the stand-alone scenario in which all companies are only responsible for serving their own customer clusters, we allow for the transfer of clusters from one partner to another partner in the coalition. In this way, we encourage that each cluster is served by the partner that can fulfil the corresponding transportation requests in the most efficient way. This is visualised in Fig. 1. Here, a two-partner coalition is represented. Both companies operate from the central depot depicted by the square. The first partner, represented in black, needs to deliver goods to customers located in four clusters (A, B, C and D) using two vehicles. The two resulting vehicle trips, obtained by solving the CluVRP for this partner, are visualised by the black edges. A similar approach can be used to calculate the optimal operational plan for the second (grey) partner in which clusters E, F, G and H are served. Even though both companies have fully optimised their own logistics operations internally, it is likely that a more efficient operational plan can be constructed when considering a horizontal cooperation. A collaborative logistics model is to be solved, taking all transportation requests of both partners into account. The following objectives are identified.

3.3. Coalition objective

In the non-collaborative definition of the CluVRP, presented in Section 3.1, the minimisation of the total distance driven by all vehicles is the main (and only) objective. By extrapolating this to the coalition, we assume that all partners agree on the common objective to reduce the total distance-based cost of the whole coalition as much as possible. This objective is referred to as the coalition objective $F_c(x)$ and is calculated as the sum of the distance-based cost of the CluVRP solution obtained for every partner.

$$F_c(x) = \sum_{p\in N}\left(\sum_{(i,j)\in E}\sum_{k\in K} d_{ij}x_{ijk}\right)_p$$

3.4. Partner objectives

With or without horizontal cooperation, the aim of each individual company will remain to deliver its customers in the most cost effective way. We therefore argue that a company is likely to prefer the solution that costs him the least. The fraction of the total coalition cost that should be paid by an individual partner is determined by the applied *cost allocation mechanism* and denoted as ψ_p. Given a predefined cost allocation method, for each partner, the partner objective is defined as the minimisation of the cost to be paid by that partner. As a result, we obtain a multi-objective optimisation model with dimensionality equal to the number of partners (n).

$$\forall p\in N : F_p(x) = \psi_p$$

4. Integrated solution approach

In the current section, the integrated solution approach for tackling collaborative logistics optimisation problems is presented.

We first introduce a general framework, after which it is further specified for the CluVRP.

4.1. General framework

We consider a horizontal logistics cooperation of n partners optimising their operational planning. The main motivation for the group to invest in this long-term relationship is given by a common goal on which all partners agree, i.e., the *coalition objective*. The following model shows the (generalised) optimisation model at the coalition level,

$$F_c(x^*) = \min(F_c(x))$$

Subject to

$$x \in \zeta$$

in which $F_c(x)$ is defined as the *coalition objective* and a solution vector $x \in \zeta$ is to be determined such that the coalition objective is minimised. We will refer to this problem as the *Coalition Level Optimisation Problem (CLOP)*. The definition of the solution space ζ will depend on the logistics problem studied. Let x^* be the best-known solution vector and $F_c(x^*)$ the corresponding value of the objective function. In the cooperative logistics context described before, x^* can be interpreted as the best possible solution for the coalition as a whole considering only the coalition objective.

Now, each collaborating company is given the opportunity to express which characteristics of the solution x it deems important. This gives rise to another set of objective functions, i.e., the *partner objectives*. These objectives, denoted as $F_i(x)$, with $i = \{1, \dots, k\}$, should assure that all partners evaluate the proposed solutions as beneficial and therefore do not have the intention to leave the coalition. Each partner is free to impose either none, a single, or multiple additional objectives to the optimisation procedure.

Let $d(a, b)$ be a distance measure between two solutions $a, b \in \zeta$, and let ϵ, be a parameter that states the acceptable deviation from the optimal coalition solution. Now, define the acceptable region of x^* as follows:

$$\mathcal{R}(x^*) = \{x | d(x, x^*) \leq \epsilon\} \tag{10}$$

The acceptable region of x^* comprises all solution vectors $x \in \zeta$ that are within a distance ϵ from x^* with respect to the coalition objective value. In this paper we will consider the distance between solutions $a, b \in \zeta$ to be equal to their difference in coalition objective value.

$$d(a, b) = |F_c(a) - F_c(b)| \tag{11}$$

We now define the *Partner Level Optimisation Problem (PLOP)* as a multi-objective optimisation problem that includes all partner objectives as follows:

$$\min_{x \in \zeta}(F_1(x), \dots, F_k(x))$$

Subject to

$$x \in \mathcal{R}(x^*)$$

According to Veldhuizen and Lamont [32], three main approaches for tackling a multi-objective optimisation problem can be distinguished: (i) *a priori preference articulation*, in which the different objectives are combined in one scalar function prior to the optimisation process whereafter a single-objective optimisation problem is solved, (ii) *progressive preference articulation*, in which the preferences of the decision maker are revealed as the search progresses, or (iii) *posteriori preference articulation*, in which the decision maker is presented a set of Pareto-optimal candidate solutions. In the setting of horizontal cooperation, the importance (weight) of an individual partner objective will likely be (partially) based on the partner's negotiation power and position in and influence on the coalition, and can therefore be considered highly case-based. For this reason, we do not want to make any assumptions on the weights before or during the optimisation process, and therefore develop a model with posteriori preference articulation.

The result of this multi-objective optimisation model is a Pareto set of non-dominated solutions with respect to the individual partner objectives. Furthermore, we assure that all reported solutions remain close to the optimal solution at the coalition level. In this way, the size of the solution space is reduced by focusing only on the most promising solutions that ensure a certain level of efficiency for the coalition as a whole. This approach also allows controlling the size of the solution set provided to the decision maker by varying the size of the acceptable region. The selection of the final solution out of the presented Pareto set could be done by means of a multi-criteria analysis, but is considered out of the scope of this paper.

As a conclusion, the general solution framework requires two optimisation problems to be solved. First, in the Coalition Level Optimisation Problem (CLOP), the routing problem is defined and solved at the level of the coalition, considering only the coalition objective. Second, the multi-objective Partner Level Optimisation Problem (PLOP), containing all individual partner objectives, is to be solved. In the following sections, both problems are studied in more detail by applying them to the collaborative CluVRP example.

4.2. CluVRP coalition level optimisation problem (CLOP)

As stated in Section 3.3, the coalition as a whole considers the minimisation of the total logistics cost as its only objective. This total coalition cost is calculated as the sum of the routing costs incurred by each individual partner in the final solution. The aim of the CLOP is therefore to determine a set of routes for each partner, in such a way that the total cost of all these routes is minimised. As we require that all vehicles are used, the number of routes allocated to each partner should equal the number of vehicles each partner has available. K^p is the set of vehicles for partner p, so the set of available vehicles at coalition level $K^c = \bigcup_{p \in N} K^p$, under the assumption that $\bigcap_{p \in N} K^p = \emptyset$. Similarly, the aggregated set of all customers that should be visited by all partners in the coalition is represented by $V^c = \bigcup_{p \in N} V^p$ in which V^p is the set of vertices that belong to partner p. Without loss of generality, it is assumed that all partners operate from the same depot (V_0) and no customers are shared. This means that each customer is linked to only one of the partners.

The goal of the CLOP is to construct $|K^c|$ vehicle routes, in such a way that all transportation requests of all partners in the coalition are executed and the total logistics cost is minimised. From the perspective of the coalition as a whole, this aggregated problem equals the classic CluVRP, and can therefore be solved by any (non-collaborative) solution technique available in the literature.

In this paper, we will make use of the two-level solution approach proposed in Defryn and Sörensen [10] as the algorithm has been proven to provide good solutions in very short calculation times. The algorithm exploits the clustered substructure of the CluVRP by dividing the problem in two, less complex, subproblems that are solved iteratively until a predefined stopping criterion is met. First, all customers belonging to the same cluster are aggregated and the CluVRP is defined and solved as a capacitated vehicle routing problem at the cluster level. The result of this phase is a sequence of clusters and forms the input for the second subproblem. Second, to create the routes at the level of the individual customers, a travelling salesman problem is solved within each cluster. Each subproblem is solved by a variable neighbourhood search

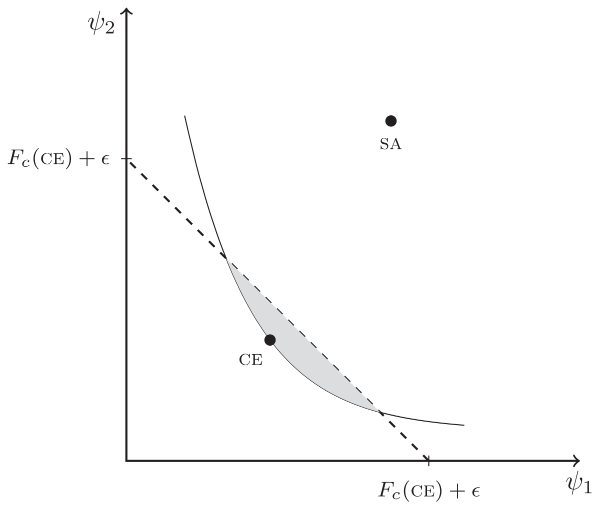


Fig. 2. Visual representation of the acceptable region $\mathcal{R}(\textsc{ce})$ of the coalition efficient solution in a two-partner coalition for our CluVRP example.

metaheuristic that makes use of the most common local search operators in vehicle routing.

The result of this phase is a single solution for the CluVRP defined at the coalition level. This solution is considered the *best possible outcome for the coalition as a whole* as it is optimised with respect to the coalition objective.

4.3. CluVRP partner level optimisation problem (PLOP)

The PLOP can be considered a multi-objective variant of the aggregated logistics optimisation problem defined in Section 4.2. The goal is to fulfil all transportation requests from all partners in the coalition in such a way that all individual partner objectives are optimised. Due to the multi-objective character of the problem, the optimal solution set is no longer a singleton, but a Pareto set of non-dominated solutions.

The solution space for the CluVRP variant studied in this paper is visualised in Fig. 2. For illustrative purposes we limit ourselves to a two-partner coalition, however our conclusions can easily be extended to instances with more than two partners. The costs allocated to partner 1 and 2 are denoted on the horizontal and vertical axis respectively. The result of the stand-alone scenario is denoted by the point SA, and point CE is the optimal result obtained by solving the CLOP. The Pareto front is represented by the solid line. Because we defined the coalition objective as the minimisation of the total cost, CE is an element of the Pareto set. This is explained by the fact that the total cost equals the sum of all costs allocated to the individual partner (in our case $F_c(\textsc{ce}) = \psi_1 + \psi_2$). Therefore, no solution exists that has a lower value for both ψ_1 and ψ_2.

4.3.1. Optimisation through cluster exchange

To ensure that all customers belonging to the same cluster remain grouped in the same vehicle, we state that only complete clusters can be exchanged between partners. Therefore, each solution for the collaborative variant of the CluVRP differs in the way the clusters are allocated to the individual partners. An allocation of all clusters to the partners is referred to as a *cluster configuration*. If Ω is the set of all possible cluster configurations, then the aim of the PLOP is to find these routing solutions resulting from cluster configurations $\omega_i \in \Omega$ for which the individual partner objectives are Pareto efficient.

To reduce the search on irrelevant parts of the solution space, and to provide the decision maker with a set of solutions that score well on both the coalition objective and the individual partner objectives, we focus only on the solutions that stay within a predefined distance ϵ from the coalition efficient solution CE and therefore belong to its acceptable region $\mathcal{R}(\textsc{ce})$, as defined in Eq. (10) and visualised by the grey zone in Fig. 2. $\mathcal{R}(\textsc{ce})$ contains all solutions for the coalition with a total logistics cost smaller than $F_c(x)+\epsilon$. Instead of constructing the whole Pareto frontier, the problem is now reduced to finding the set of non-dominated solutions that belong to $\mathcal{R}(\textsc{ce})$. This means that for the CluVRP the problem is reduced to approximating only the part of the Pareto frontier that forms the border of $\mathcal{R}(\textsc{ce})$. As we expect very similar configurations to result into a comparable total coalition cost, we propose a local search based approach to explore alternative cluster configurations.

Table 2
Definition of the local search neighbourhoods used for exchanging the clusters.

Neighbourhood	Definition
Swap	Swap the partner of two clusters.
Relocate	Change the partner of one of the clusters.

4.3.2. Search strategy

To approximate the part of the Pareto frontier that belongs to $\mathcal{R}(\textsc{ce})$, we make use of an iterative procedure. At each iteration, all cluster configurations in the current Pareto optimal solutions are explored with respect to the neighbourhoods defined in Table 2.

By changing the subset of clusters to be visited by each partner, the routing solution should be re-optimised by solving a CluVRP for every (affected) partner. As this is done for every cluster configuration that can be reached from all solutions currently in the Pareto frontier for a given neighbourhood, a set of alternative but very similar routing solutions is generated (the difference in cluster configurations is only one move, and the operators are not very disruptive). Because of this similarity, we also expect the total cost of these new solutions to be relatively close to the total cost of the initial Pareto efficient solution, so it is likely that these new solutions belong to $\mathcal{R}(\textsc{ce})$.

5. Computational experiments

5.1. Benchmark instances

In the literature, no benchmark instances are available for a multi-partner CluVRP as this problem has never been studied before. We therefore adapt the GVRPθ3 (set A) instances provided by Battarra et al. [5] for the traditional CluVRP to comply with the multi-partner environment by including the following additional specifications. Coalitions with up to four partners are considered ($n \in \{2, 3, 4\}$). It is ensured that the grand coalition size is at most equal to the total number of available vehicles ($|K^c|$) so each partner has at least one vehicle. Furthermore, each cluster is allocated to only one partner. This is done in a random way to avoid that all clusters that belong to the same partner are geographically grouped in the same part of the distribution area. However, the feasibility of the stand-alone scenario is guaranteed by making sure that for each partner enough vehicle capacity is available to serve at least the demand of its own clusters. The instances are labelled according to the parameters listed in Table 3. In total, 43 different instances are constructed, which are available upon request.

Table 3
Instance parameters.

Parameter	Definition
n	Number of nodes (including a single depot)
k	Number of vehicles in the original CVRP variant of the instance
C	Number of clusters
V	Number of vehicles in the CluVRP instance
P	Number of partners in the cooperation

5.2. Cost allocation method

To divide the cost of a shared vehicle trip among all partners involved, a volume-based allocation rule is applied. This method divides the total coalition cost proportionally to the demand of each partner in the current vehicle trip. For each vehicle trip $k \in K^c$, the total cost allocated to partner p is calculated according to Eq. (12).

$$\psi_p = \frac{\sum_{i \in V^p} q_i y_{ik}}{\sum_{i \in V^c} q_i y_{ik}} \sum_{(i,j) \in E} d_{ij} x_{ijk} \tag{12}$$

The volume-based allocation rule is selected because it is straightforward and often used in industry. This is, however, at the expense of certain properties defined in game theory, such as individual rationality and stability [31]. Choosing another cost allocation mechanism is likely to significantly alter the allocation results and therefore all numerical results presented, however this will not affect the general conclusions drawn in this paper. It should be noted that, when selecting a proportional allocation rule for which the weights do not vary for different collaborative solutions (e.g., proportional to the partners' stand-alone costs, or rather than allocating the cost of each vehicle trip the total coalition cost is divided based on the partners' shipped volumes), the size of the Pareto-set will always equal 1 for our CluVRP example. This is due to the fact that with fixed weights a larger total coalition cost will by definition increase the cost allocated to every partner. As a result, all partners will always prefer the coalition-efficient solution to minimise their own cost.

5.3. Definition of the acceptable region

As defined in (10) and (11), the acceptable region depends on the parameter ϵ, which is to be determined by the collaborating partners and represents the maximum allowed difference in coalition objective compared to the coalition-efficient solution. To enable the comparison between different instances, we define ϵ relative to the value of the coalition objective in the coalition-efficient solution.

$$\epsilon = \alpha \times F_c(\textsc{ce}) \tag{13}$$

In this formula, α equals the maximum relative increase for the coalition objective that will be accepted by the coalition. The value of α should be interpreted as follows: for $\alpha = 0.05$, the coalition is willing to accept solutions for which the total distance driven by all vehicles has not increased more than 5% compared to the coalition-efficient solution.

The higher the value of α, the more solutions in the acceptable region. This increases the probability that better solutions can be found with respect to the individual partner objectives, but also lowers the quality of the solutions at the coalition level and therefore reduces the added value of setting up a horizontal cooperation.

5.4. Simulation results

The integrated solution framework is tested on the set of generated benchmark instances. Three different scenarios are considered in which the coalition accepts a 1%, 5% or 10% increase in total distance driven by all vehicles compared to the coalition-efficient solution, which is equivalent to setting the parameter α equal to 0.01, 0.05 or 0.1 respectively. All results for $\alpha = 0.05$ are presented in Tables 4 and 5. For detailed experimental results for all other scenarios, we refer the reader to Appendix A.

For the grand coalition, the summed stand-alone cost of all partners is given in column SA and the total cost of the best solution at the coalition level is listed in column CE. Our results confirm that setting up a horizontal logistics cooperation is beneficial as double-digit profits are obtained for almost all instances. For the two-partner instances, the average coalition profit is around 16.5%. For the three- and four-partner instances these potential profits increase to around 26% and 34.5% respectively. This increase is explained by the fact that larger coalitions can create more opportunities for optimisation. For every partner p the relative profit is calculated by comparing its stand-alone cost $c(\textsc{sa}_p)$ with the allocated cost ψ_p according to Eq. (14).

$$\text{profit}(\%) = \frac{c(\textsc{sa}_p) - \psi_p}{c(\textsc{sa}_p)} \tag{14}$$

The profit realised by each partner when choosing the coalition efficient solution is denoted in its column CE. The columns MIN and MAX give the range in which the relative profit of the partner varies over all Pareto-efficient solutions returned by the proposed solution framework. It can be seen that for instances with a Pareto-size of 1, the coalition efficient solution CE is the most profitable option for all partners, as no alternative solution could be found within the acceptable region $\mathcal{R}(\textsc{ce})$ that is Pareto-efficient with respect to all individual partner objectives. In all other scenarios, at least one partner is able to improve its situation by selecting another solution from the Pareto set. Consider for example instance *n33-k5-C11-V2-p2* in Table 4. The relative profit realised by partner two when selecting the coalition-efficient solution is 17%. The MAX column, however, shows that the partner's personal profit can increase up to 20% by selecting an alternative solution from the Pareto set.

For all instances marked with a ✗, the coalition-efficient solution is even suboptimal for all partners in the coalition. This means that from the list of alternative solutions, each partner will prefer a solution that is different from CE (i.e., the solution scores better on the partner's individual objective). However, different partners might (and in our CluVRP example, will) prefer other solutions.

For some instances (e.g., *n39-k6-C13-V2-p2* and *n62-k8-C21-V3-p2* in Table 4), the differences in the values of the partner objectives over all Pareto efficient solutions are smaller than 1% for each individual partner. In such situation, the partners are likely to be indifferent with respect to all Pareto-efficient solutions. These additional insights in the sensitivity of a solution, gained by providing a set of high-quality alternative solutions instead of only CE, can support the decision making process.

The higher the value of α, the larger the acceptable region $\mathcal{R}(\textsc{ce})$ and the higher the probability that all partners can improve their individual situation by diverging from the coalition-efficient solution. Furthermore, we notice that although all solutions guarantee that the global efficiency of the coalition is high (only solutions in the acceptable region $\mathcal{R}(\textsc{ce})$ are considered), individual differences for the partners can be significant. For example in instance *n33-k6-C11-V2-p2*, the relative profit margin for partner 2 ranges from -10% up to 16%. These results acknowledge the importance of including individual partner preferences into the optimisation procedure.

Although not guaranteed by the volume-based allocation rule, almost all solutions satisfy the property of individual rationality. Regardless of the allocation rule used, our framework generates

Table 4
Detailed results for the two-partner ColGVRPθ3 instances with $\alpha = 0.05$.

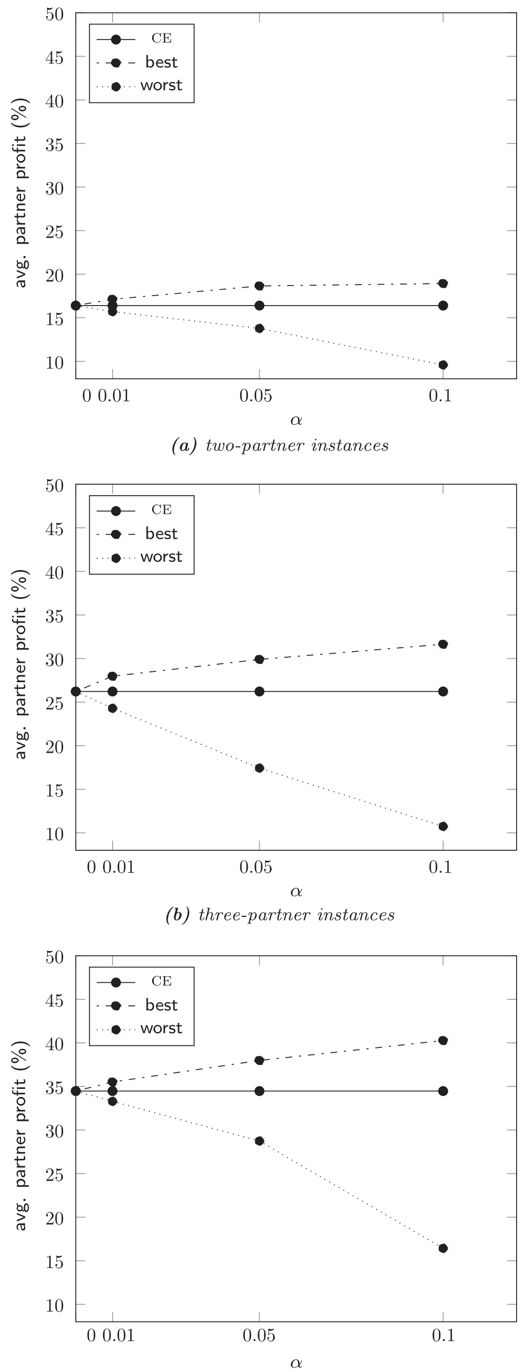
Instance					Grand coalition			Partner 1			Partner 2			Pareto set	
n	k	C	V	p	Total cost		Max.	Profit			Profit			Size	
					SA	CE	profit	CE	min	max	CE	min	max		
32	5	11	2	2	634	522	18%	**15%**	15%	15%	**22%**	22%	22%	1	
33	5	11	2	2	578	472	18%	**19%**	15%	19%	17%	14%	20%	3	
33	6	11	2	2	676	562	17%	24%	16%	27%	6%	−10%	16%	4	✗
34	5	12	2	2	651	547	16%	**25%**	23%	25%	5%	5%	7%	2	
36	5	12	2	2	746	589	21%	**26%**	26%	26%	**15%**	15%	15%	1	
37	5	13	2	2	677	569	16%	17%	17%	18%	**15%**	8%	15%	2	
37	6	13	2	2	733	615	16%	21%	21%	23%	**10%**	6%	10%	3	
38	5	13	2	2	692	507	27%	**37%**	37%	37%	**13%**	13%	13%	1	
39	5	13	2	2	751	618	18%	33%	33%	35%	**−1%**	−2%	−1%	3	
39	6	13	2	2	765	613	20%	**33%**	33%	33%	**0%**	−5%	0%	2	
44	6	15	2	2	811	729	10%	−1%	−2%	3%	19%	18%	23%	3	✗
45	6	15	3	2	776	712	8%	14%	2%	16%	−2%	−9%	8%	8	✗
45	7	15	3	2	818	664	19%	**13%**	13%	13%	**29%**	29%	29%	1	
46	7	16	3	2	801	664	17%	18%	16%	24%	15%	1%	17%	11	✗
48	7	16	3	2	836	683	18%	15%	15%	19%	**23%**	16%	23%	4	
53	7	18	3	2	817	651	20%	17%	16%	21%	**24%**	16%	24%	5	
54	7	18	3	2	873	724	17%	15%	6%	16%	20%	13%	30%	8	✗
55	9	19	3	2	795	653	18%	**14%**	11%	14%	**25%**	25%	25%	2	
60	9	20	3	2	904	795	12%	**8%**	4%	8%	19%	21%	22%	2	
61	9	21	4	2	832	682	18%	**26%**	15%	26%	11%	11%	14%	6	
62	8	21	3	2	910	778	15%	**12%**	12%	12%	**20%**	9%	20%	4	
63	9	21	3	2	1029	865	16%	10%	2%	9%	26%	25%	29%	4	✗
63	10	21	4	2	994	801	19%	**29%**	29%	29%	**10%**	10%	10%	1	
64	9	22	3	2	906	776	14%	**18%**	10%	18%	8%	8%	14%	7	
65	9	22	3	2	839	749	11%	6%	8%	8%	18%	22%	22%	1	✗
69	9	23	3	2	931	839	10%	1%	−7%	10%	23%	8%	32%	17	✗
80	10	27	4	2	1197	974	19%	36%	26%	38%	−1%	−8%	6%	17	✗

Table 5
Detailed results for the ColGVRPθ3 instances with more than two partners with $\alpha = 0.05$.

Instance					Grand coalition			Partner 1			Partner 2			Partner 3			Partner 4			Pareto set	
n	k	C	V	p	Total cost		Max.	Profit			Profit			Profit			Profit			Size	
					SA	CE	profit	CE	min	max	CE	min	max	CE	min	max	CE	min	max		
45	6	15	3	3	999	712	29%	58%	51%	59%	−2%	−17%	8%	14%	0%	20%				11	✗
45	7	15	3	3	938	664	29%	31%	26%	37%	**29%**	17%	29%	**27%**	13%	27%				8	
46	7	16	3	3	947	664	30%	55%	42%	57%	15%	−1%	17%	14%	8%	25%				33	✗
48	7	16	3	3	960	683	29%	41%	32%	43%	**23%**	8%	23%	22%	17%	30%				24	✗
53	7	18	3	3	986	651	34%	46%	39%	49%	24%	16%	26%	32%	25%	37%				28	✗
54	7	18	3	3	997	724	27%	**22%**	10%	22%	20%	13%	26%	43%	40%	51%				13	
55	9	19	3	3	998	653	35%	**44%**	42%	44%	25%	25%	26%	**33%**	25%	33%				5	
60	9	20	3	3	1051	795	24%	**29%**	26%	29%	19%	18%	22%	24%	22%	25%				10	
62	8	21	3	3	1050	778	26%	**38%**	33%	38%	**20%**	9%	20%	15%	11%	20%				18	
63	9	21	3	3	1076	895	17%	12%	4%	14%	25%	15%	26%	12%	10%	15%				9	✗
64	9	22	3	3	1101	779	29%	39%	29%	42%	8%	0%	14%	36%	22%	42%				42	✗
65	9	22	3	3	996	796	20%	35%	20%	40%	8%	−3%	26%	13%	5%	22%				32	✗
69	9	23	3	3	1052	829	21%	26%	12%	29%	23%	18%	33%	13%	−4%	19%				38	✗
61	9	21	4	4	1134	682	40%	53%	50%	58%	46%	38%	47%	**43%**	33%	43%	13%	8%	20%	23	
63	10	21	4	4	1217	801	34%	**54%**	48%	54%	30%	21%	32%	13%	10%	15%	32%	23%	34%	4	

a set of alternative solutions which can help the decision makers to select a solution from the Pareto set that contributes most to the long-term stability and success of the collaboration. In instance *n45-k6-C15-V3-p2*, e.g., the coalition-efficient solution is not stable (a negative profit is allocated to partner 2), but there exist alternative solutions in the Pareto set of the acceptable region that guarantee stability for this cooperation. If such a solution would not be available (see, e.g., instance *n39-k5-C13-V2-p2* in which the profit for partner 2 is always negative), the cooperation might not be viable within the initial agreements made (i.e., coalition objective, individual partner objectives and/or allocation rule). As the operational problem presented in this paper is solved on a daily basis (or even more frequently) by the collaborating partners, it should be questioned whether the property of individual rationality is violated only rarely or on a regular basis. In the latter case, the partners can renegotiate the agreements governing the collaboration (e.g., by negotiating a different allocation rule, by changing the composition of the consortium,...).

The effect of parameter α on the constructed Pareto frontier is visualised in Fig. 3. In this figure, the average profit obtained by choosing the coalition efficient solution is compared by respectively the best and the worst average profit for an individual partner over all instances. When α equals zero, the acceptable region $\mathcal{R}(\text{CE})$ contains only CE. For increasing values of α, the results for each individual partner start to diverge significantly. We also observe that the difference in individual profit tends to be more sensitive in the negative direction. This was expected as all solutions have a total coalition cost that is higher than the cost of solution CE. Our results show that a small change in the solution, with relatively limited impact on the coalition objective, might have a significant impact on the objective function of the partners in the coalition. A change in total coalition cost of maxi-



(a) two-partner instances

(b) three-partner instances

(c) four-partner instances

Fig. 3. Average partner profit for all solutions in the Pareto set.

mum 5% ($\alpha = 0.05$) results in a solution set in which the cost allocated to an individual partner differs by 5.87% on average. For a three- and four-partner coalition, these individual differences increase to 12.46% and 9.25% respectively.

6. Conclusions and further research

Existing research on horizontal logistics cooperation has mainly focused on assessing costs and benefits, and their allocation to individual collaborating partners. Our literature review has shown that all existing contributions study the logistics optimisation model from the perspective of the coalition. Individual partner interests are either taken into account as an independent step or are not considered at all. This paper is the first to propose a modelling framework and solution method to explicitly take both coalition level objectives and partner level objectives into account within the context of horizontal logistics cooperation.

With the growing importance of e-commerce, today's distribution systems are under high pressure which motivates more and more companies to engage in a collaboration. To focus ideas, a horizontal logistics cooperation is considered in which up to four companies jointly optimise their logistics operations. The collaboration is modelled as a clustered vehicle routing problem, in which customers belonging to a predefined cluster are served consecutively by the same vehicle.

A multi-partner logistics optimisation framework is proposed that allows each individual partner to express its (individual) objectives, additional to a global objective that is defined at the coalition level. The framework requires two optimisation problems to be solved sequentially, referred to as the coalition level optimisation problem (CLOP) and the partner level optimisation problem (PLOP) respectively. Similar to the existing approaches studied in our literature review, in the CLOP the logistics optimisation problem is studied only from the perspective of the coalition, as all transportation requests of all partners are aggregated and only the coalition objective is considered. As we assumed in our CluVRP example the coalition objective to be single-objective, the coalition-efficient solution CE was a unique solution. The framework, however, could easily be extended to allow multiple coalition objectives for which a Pareto set of coalition-efficient solutions can be found. The PLOP is essentially a multi-objective variant of the CLOP in which all individual partner objectives are considered and an additional constraint is introduced that limits the search to only solutions within the acceptable region of the coalition-efficient solution. Due to its higher dimensionality, the PLOP tends to be more complex compared to the CLOP. A heuristic solution procedure is proposed for the PLOP that iteratively explores the neighbourhood of the current Pareto set.

We conducted extensive computational experiments for the CluVRP on a set of benchmark instances from the literature that we adapted to comply with the multi-partner context. We observed that, even if horizontal cooperation is beneficial for the coalition (double-digit savings are obtained for almost all instances), a slightly inferior solution for the group as a whole might result into (much) better solutions for one or more partners in the coalition. Moreover, we showed that for a large number of instances, the coalition-efficient solution was actually inferior for all partners in the cooperation. This means that every partner had the incentive to deviate from the coalition-efficient solution, as this would generate a better value for its personal objective. Unlike currently existing methods in the literature, we are able to provide decision makers with a set of alternative solutions which provide additional insight into the sensitivity of both the coalition objective(s) and the individual partner objectives. As daily operations in practice might be subject to unexpected changes, and transportation patterns are likely to evolve over time, this extra information might contribute to higher long-term stability and success of the collaboration.

However, including partner objectives increases the complexity of the logistics optimisation problem. We believe that this offers interesting avenues for further research. First, as our solution framework will provide the decision makers with a set of alternative solutions, a single final solution should be selected afterwards. This could be done by means of a multi-criteria analysis. the result of this multi-criteria analysis will (partly) be based on the importance (weight) of each individual partner objective and therefore also on the partner's negotiation power and its position in and influence on the coalition. Second, it might be interesting to extend our simulation study and compare the results for different cost allocation methods. The same goes for the use of different types and combinations of objective functions (e.g., minimisation of time window violations, route balancing, ...), both at the coalition and the individual partner level.

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Appendix A. Detailed results overview

Table A6
Detailed results for the two-partner CoLGVRPθ3 instances with $\alpha = 0.01$.

Instance					Grand coalition			Partner 1			Partner 2			Pareto set	
n	k	C	V	p	Total cost		Max.	Profit			Profit			Size	
					SA	CE	profit	CE	min	max	CE	min	max		
32	5	11	2	2	634	522	18%	**15%**	15%	15%	**22%**	22%	22%	1	
33	5	11	2	2	578	472	18%	19%	19%	20%	**17%**	14%	17%	2	
33	6	11	2	2	676	562	17%	**24%**	24%	24%	**6%**	6%	6%	1	
34	5	12	2	2	651	547	16%	**25%**	23%	25%	5%	5%	7%	2	
36	5	12	2	2	746	589	21%	**26%**	26%	26%	**15%**	15%	15%	1	
37	5	13	2	2	677	569	16%	**17%**	17%	17%	**15%**	15%	15%	1	
37	6	13	2	2	733	615	16%	**21%**	21%	21%	**10%**	10%	10%	2	
38	5	13	2	2	692	507	27%	**37%**	37%	37%	**13%**	13%	13%	1	
39	5	13	2	2	751	618	18%	33%	33%	35%	**−1%**	−2%	−1%	3	
39	6	13	2	2	765	613	20%	**33%**	33%	33%	**0%**	0%	0%	1	
44	6	15	2	2	811	733	10%	**6%**	6%	6%	**12%**	12%	12%	1	
45	6	15	3	2	776	712	8%	**14%**	13%	14%	−2%	−2%	−1%	2	
45	7	15	3	2	818	664	19%	13%	13%	14%	**29%**	24%	29%	2	
46	7	16	3	2	801	664	17%	18%	18%	19%	**15%**	13%	15%	2	
48	7	16	3	2	836	683	18%	15%	15%	19%	**23%**	16%	23%	3	
53	7	18	3	2	817	651	20%	**17%**	17%	17%	**24%**	24%	24%	1	
54	7	18	3	2	873	724	17%	15%	15%	16%	**20%**	19%	20%	2	
55	9	19	3	2	795	653	18%	**14%**	14%	14%	**25%**	25%	25%	1	
60	9	20	3	2	904	795	12%	**8%**	8%	8%	19%	18%	21%	2	
61	9	21	4	2	832	682	18%	**26%**	25%	26%	**11%**	11%	11%	3	
62	8	21	3	2	910	778	15%	**12%**	12%	12%	**20%**	17%	20%	3	
63	9	21	3	2	1058	906	14%	**10%**	10%	10%	**23%**	23%	23%	1	
63	10	21	4	2	994	801	19%	**29%**	29%	29%	**10%**	9%	10%	2	
64	9	22	3	2	906	776	14%	**18%**	18%	18%	**8%**	8%	8%	1	
65	9	22	3	2	864	739	14%	**12%**	12%	12%	**18%**	18%	18%	1	
69	9	23	3	2	931	838	10%	2%	−4%	8%	22%	14%	32%	17	✗
80	10	27	4	2	1197	977	18%	**34%**	34%	34%	**1%**	1%	1%	1	

Table A7
Detailed results for the CoLGVRPθ3 instances with more than two partners with $\alpha = 0.01$.

Instance					Grand coalition			Partner 1			Partner 2			Partner 3			Partner 4			Pareto set	
n	k	C	V	p	Total cost		Max.	Profit			Profit			Profit			Profit			Size	
					SA	CE	profit	CE	min	max	CE	min	max	CE	min	max	CE	min	max		
45	6	15	3	3	999	712	29%	**58%**	57%	58%	−2%	−2%	−1%	**14%**	13%	14%				2	
45	7	15	3	3	938	664	29%	31%	31%	36%	**29%**	24%	29%	**27%**	25%	27%				2	
46	7	16	3	3	947	664	30%	**55%**	53%	55%	**15%**	9%	15%	14%	14%	19%				4	
48	7	16	3	3	960	683	29%	**41%**	40%	41%	**23%**	20%	23%	22%	22%	25%				2	
53	7	18	3	3	986	651	34%	**46%**	46%	46%	**24%**	24%	24%	**32%**	32%	32%				1	
54	7	18	3	3	997	724	27%	**22%**	18%	22%	**20%**	19%	20%	43%	43%	51%				2	
55	9	19	3	3	998	653	35%	**44%**	44%	44%	**25%**	25%	25%	**33%**	32%	33%				2	
60	9	20	3	3	1051	795	24%	**29%**	28%	29%	19%	18%	21%	24%	23%	25%				3	
62	8	21	3	3	1050	778	26%	**38%**	38%	38%	**20%**	17%	20%	15%	15%	16%				3	
63	9	21	3	3	1076	895	17%	12%	6%	14%	**25%**	19%	25%	12%	6%	17%				21	
64	9	22	3	3	1101	795	28%	37%	33%	41%	7%	4%	14%	35%	27%	41%				26	✗
65	9	22	3	3	996	751	25%	38%	38%	40%	19%	20%	22%	12%	12%	17%				2	✗
69	9	23	3	3	1052	820	22%	**27%**	23%	27%	28%	23%	29%	9%	9%	17%				9	
61	9	21	4	4	1134	682	40%	**53%**	53%	53%	46%	45%	47%	**43%**	42%	43%	13%	12%	14%	6	
63	10	21	4	4	1217	801	34%	**54%**	53%	54%	30%	30%	31%	**13%**	10%	13%	32%	32%	33%	2	

Table A8
Detailed results for the two-partner CoLGVRPθ3 instances with $\alpha = 0.1$.

Instance					Grand coalition			Partner 1			Partner 2			Pareto set	
n	k	C	V	p	Total cost		Max.	Profit			Profit			Size	
					SA	CE	profit	CE	min	max	CE	min	max		
32	5	11	2	2	634	522	18%	**15%**	15%	15%	**22%**	22%	22%	1	
33	5	11	2	2	578	472	18%	19%	5%	20%	17%	14%	22%	5	✗
33	6	11	2	2	676	562	17%	24%	16%	27%	6%	−10%	16%	5	✗
34	5	12	2	2	651	547	16%	**25%**	23%	25%	5%	5%	7%	2	
36	5	12	2	2	746	589	21%	**26%**	26%	26%	**15%**	15%	15%	1	
37	5	13	2	2	677	569	16%	17%	17%	18%	**15%**	2%	15%	3	
37	6	13	2	2	733	615	16%	21%	21%	23%	**10%**	6%	10%	3	
38	5	13	2	2	692	507	27%	**37%**	22%	37%	13%	13%	16%	4	
39	5	13	2	2	751	618	18%	33%	13%	35%	−1%	−2%	7%	9	✗
39	6	13	2	2	765	613	20%	**33%**	33%	33%	**0%**	−5%	0%	2	
44	6	15	2	2	811	729	10%	**−1%**	−1%	−1%	**19%**	19%	19%	1	
45	6	15	3	2	776	712	8%	14%	−8%	16%	−2%	−9%	12%	10	✗
45	7	15	3	2	818	664	19%	13%	13%	16%	**29%**	7%	29%	4	
46	7	16	3	2	801	664	17%	18%	16%	22%	15%	6%	16%	7	✗
48	7	16	3	2	836	683	18%	15%	15%	19%	**23%**	9%	23%	4	
53	7	18	3	2	817	651	20%	17%	7%	21%	24%	16%	25%	9	✗
54	7	18	3	2	873	724	17%	15%	−4%	16%	20%	13%	30%	19	✗
55	9	19	3	2	795	653	18%	**14%**	11%	14%	**25%**	25%	25%	2	
60	9	20	3	2	904	795	12%	**8%**	−5%	8%	19%	18%	22%	11	
61	9	21	4	2	832	682	18%	**26%**	15%	26%	11%	11%	14%	6	
62	8	21	3	2	910	778	15%	12%	8%	13%	**20%**	11%	20%	6	
63	9	21	3	2	1029	865	16%	10%	0%	13%	26%	2%	29%	12	✗
63	10	21	4	2	994	801	19%	**29%**	10%	29%	10%	1%	13%	5	
64	9	22	3	2	906	776	14%	**18%**	3%	18%	8%	8%	15%	9	
65	9	22	3	2	839	749	11%	6%	8%	8%	18%	22%	22%	1	✗
69	9	23	3	2	931	839	10%	1%	−5%	12%	23%	9%	31%	17	✗
80	10	27	4	2	1197	976	18%	35%	16%	38%	0%	−7%	9%	28	✗

Table A9
Detailed results for the CoLGVRPθ3 instances with more than two partners with $\alpha = 0.1$.

Instance					Grand coalition			Partner 1			Partner 2			Partner 3			Partner 4			Pareto set	
n	k	C	V	p	Total cost		Max.	Profit			Profit			Profit			Profit			Size	
					SA	CE	profit	CE	min	max	CE	min	max	CE	min	max	CE	min	max		
45	6	15	3	3	999	712	29%	58%	27%	60%	−2%	−31%	12%	14%	−7%	27%				71	✗
45	7	15	3	3	938	664	29%	31%	26%	38%	**29%**	7%	29%	27%	13%	30%				20	
46	7	16	3	3	947	664	30%	55%	34%	57%	15%	−11%	20%	14%	−5%	27%				68	✗
48	7	16	3	3	960	683	29%	41%	26%	43%	23%	3%	24%	22%	10%	33%				39	✗
53	7	18	3	3	986	651	34%	46%	32%	49%	24%	9%	26%	32%	25%	42%				46	✗
54	7	18	3	3	997	724	27%	22%	0%	26%	20%	0%	30%	43%	22%	51%				33	✗
55	9	19	3	3	998	653	35%	**44%**	42%	44%	25%	25%	26%	**33%**	25%	33%				5	
60	9	20	3	3	1051	795	24%	**29%**	26%	29%	19%	18%	22%	24%	22%	25%				10	
62	8	21	3	3	1050	778	26%	38%	21%	39%	**20%**	0%	20%	15%	11%	23%				57	
63	9	21	3	3	1076	909	16%	12%	−5%	20%	15%	−3%	28%	19%	−1%	26%				70	✗
64	9	22	3	3	1101	785	29%	37%	18%	45%	8%	−22%	17%	37%	10%	47%				217	✗
65	9	22	3	3	996	726	27%	39%	33%	40%	**22%**	5%	22%	17%	12%	20%				6	
69	9	23	3	3	1052	820	22%	27%	4%	29%	28%	10%	34%	9%	−10%	20%				69	✗
61	9	21	4	4	1134	682	40%	53%	36%	58%	46%	22%	49%	43%	17%	48%	13%	−12%	27%	404	✗
63	10	21	4	4	1217	801	34%	**54%**	34%	54%	30%	17%	32%	13%	1%	21%	32%	15%	34%	18	

References

[1] Adenso-Díaz B, Lozano S, Garcia-Carbajal S, Smith-Miles K. Assessing partnership savings in horizontal cooperation by planning linked deliveries. Transp Res Part A 2014;66:268–79.

[2] Adenso-Díaz B, Lozano S, Moreno P. Analysis of the synergies of merging multi-company transportation needs. Transportmetrica A 2014;10(6):533–47.

[3] Audy J-F, D'Amours S, Rousseau L-M. Cost allocation in the establishment of a collaborative transportation agreementan application in the furniture industry. J Oper Res Soc 2011;62(6):960–70.

[4] Bailey E, Unnikrishnan A, Lin D-Y. Models for minimizing backhaul costs through freight collaboration. Transp Res Rec 2011(2224):51–60.

[5] Battarra M, Erdoğan G, Vigo D. Exact algorithms for the clustered vehicle routing problem. Oper Res 2014;62(1):58–71.

[6] Berger S, Bierwirth C. Solutions to the request reassignment problem in collaborative carrier networks. Transp Res Part E 2010;46(5):627–38.

[7] Cruijssen F, Bräysy O, Dullaert W, Fleuren H, Salomon M. Joint route planning under varying market conditions. Int J Phys DistribLogist Manage 2007;37(4):287–304.

[8] Dahl S, Derigs U. Cooperative planning in express carrier networksan empirical study on the effectiveness of a real-time decision support system. Decis Support Syst 2011;51(3):620–6.

[9] Dai B, Chen H. A multi-agent and auction-based framework and approach for carrier collaboration. Logist Res 2011;3(2–3):101–20.

[10] Defryn C, Sörensen K. A fast two-level variable neighborhood search for the clustered vehicle routing problem. Comput Oper Res 2017;83:78–94.

[11] Defryn C, Sörensen K. Multi-objective optimisation models for the travelling salesman problem with horizontal cooperation, in review.

[12] Defryn C, Vanovermeire C, Sörensen K. Gain sharing in horizontal logistic co-operation: a case study in the fresh fruit and vegetables sector. In: Contributions to management science. Springer International Publishing; 2015. p. 75–89.

[13] Defryn C, Sörensen K, Cornelissens T. The selective vehicle routing problem in a collaborative environment. Eur J Oper Res 2016;250(2):400–11.

[14] Expósito-Izquierdo C, Rossi A, Sevaux M. A two-level solution approach to solve the clustered capacitated vehicle routing problem. Comput Ind Eng 2016;91:274–89.

[15] Flisberg P, Frisk M, Rönnqvist M, Guajardo M. Potential savings and cost allocations for forest fuel transportation in sweden: a country-wide study. Energy 2015;85:353–65.

[16] Frisk M, Göthe-Lundgren M, Jörnsten K, Rönnqvist M. Cost allocation in collaborative forest transportation. Eur J Oper Res 2010;205(2):448–58.
[17] Guajardo M, Rönnqvist M. A review on cost allocation methods in collaborative transportation. Int Trans Oper Res 2016;23(3):371–92.
[18] Guajardo M, Jörnsten K, Rönnqvist M. Constructive and blocking power in collaborative transportation. OR Spectr 2016;38(1):25–50.
[19] Hezarkhani B, Slikker M, Woensel TV. A competitive solution for cooperative truckload delivery. OR Spectr 2016;38(1):51–80.
[20] Janssens J, Bergh JVd, Sörensen K, Cattrysse D. Multi-objective microzone-based vehicle routing for courier companies: from tactical to operational planning. Eur J Oper Res 2015;242(1):222–31.
[21] Juan AA, Faulin J, Pérez-Bernabeu E, Jozefowiez N. Horizontal cooperation in vehicle routing problems with backhauling and environmental criteria. Procedia-Social Behav Sci 2014;111:1133–41.
[22] Kimms A, Kozeletskyi I. Shapley value-based cost allocation in the cooperative traveling salesman problem under rolling horizon planning. EURO J Transp Logist 2016;5(4):371–92.
[23] Kimms A, Kozeletskyi I. Core-based cost allocation in the cooperative traveling salesman problem. Eur J Oper Res 2016;248(3):910–16.
[24] Krajewska MA, Kopfer H, Laporte G, Ropke S, Zaccour G. Horizontal cooperation among freight carriers: request allocation and profit sharing. J Oper Res Soc 2008;59(11):1483–91.
[25] Li J, Rong G, Feng Y. Request selection and exchange approach for carrier collaboration based on auction of a single request. Transp Res Part E 2015;84:23–39.
[26] Lin J-R, Yan S, Lai C. International express courier routing and scheduling under uncertain demands. Eng Optim 2013;45(7):881–97.
[27] Lozano S, Moreno P, Adenso-Díaz B, Algaba E. Cooperative game theory approach to allocating benefits of horizontal cooperation. Eur J Oper Res 2013;229(2):444–52.
[28] Mourgaya M, Vanderbeck F. Column generation based heuristic for tactical planning in multi-period vehicle routing. Eur J Oper Res 2007;183(3):1028–41.
[29] Pérez-Bernabeu E, Juan AA, Faulin J, Barrios BB. Horizontal cooperation in road transportation: a case illustrating savings in distances and greenhouse gas emissions. Int Trans Oper Res 2015;22(3):585–606.
[30] Sevaux M, Sörensen K. Hamiltonian paths in large clustered routing problems. In: Proceedings of the EU/MEeting 2008 workshop on metaheuristics for logistics and vehicle routing, EU/ME, vol. 8; 2008. p. 411–17.
[31] Tijs SH, Driessen TS. Game theory and cost allocation problems. Manage Sci 1986;32(8):1015–28.
[32] Veldhuizen DAV, Lamont GB. Multiobjective evolutionary algorithms: analyzing the state-of-the-art. Evol Comput 2000;8(2):125–47.
[33] Vanovermeire C.. Horizontal collaboration in logistics. increasing efficiency through flexibility, gain sharing and collaborative planning. Phd thesis; University of Antwerp; 2014.
[34] Vanovermeire C, Sörensen K. Integration of the cost allocation in the optimization of collaborative bundling. Transp Res Part E 2014;72:125–43.
[35] Vanovermeire C, Sörensen K, Breedam AV, Vannieuwenhuyse B, Verstrepen S. Horizontal logistics collaboration: decreasing costs through flexibility and an adequate cost allocation strategy. Int J Logist Res Appl 2014;17(4):339–55.
[36] Vanovermeire C, Vercruysse D, sörensen K. Analysis of different cost allocation methods in a collaborative transport setting. Int J Eng Manage Econ 2014;4(2):132–50.
[37] Verdonck L, Caris A, Ramaekers K, Janssens GK. Collaborative logistics from the perspective of road transportation companies. Transp Rev 2013;33(6):700–19.
[38] Verdonck L, Beullens P, Caris A, Ramaekers K, Janssens GK. Analysis of collaborative savings and cost allocation techniques for the cooperative carrier facility location problem. J Oper Res Soc 2016;67(6):853–71.
[39] Wang X, Kopfer H. Collaborative transportation planning of less-than-truckload freight. OR Spectr 2014;36(2):357–80.
[40] Wang X, Kopfer H. Rolling horizon planning for a dynamic collaborative routing problem with full-truckload pickup and delivery requests. Flexible Serv Manuf J 2015;27(4):509–33.
[41] Wang Y, Ma X, Xu M, Wang L, Wang Y, Liu Y. A methodology to exploit profit allocation in logistics joint distribution network optimization. Math Problems Eng 2015;2015.
[42] Yang F, Yang M, Xia Q, Liang L. Collaborative distribution between two logistics service providers. Int Trans Oper Res 2015.
[43] Yin P-Y, Lyu S-R, Chuang Y-L. Cooperative coevolutionary approach for integrated vehicle routing and scheduling using cross-dock buffering. Eng Appl Artif Intell 2016;52:40–53.
[44] Zibaei S, Hafezalkotob A, Ghashami SS. Cooperative vehicle routing problem: an opportunity for cost saving. J Ind Eng Int 2016;12(3):271–86.
[45] Zolezzi JM, Rudnick H. Transmission cost allocation by cooperative games and coalition formation. IEEE Trans Power Syst 2002;17(4):1008–15.